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Biological Resource Allocation Algorithms for Heterogeneous Uplink PD-SCMA NOMA Networks

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ABSTRACT Due to their ability to multiplex users on a resource element (RE), Non-orthogonal multiple access (NOMA) techniques have gained popularity in 5G network implementation. The features of 5G heterogeneous networks have necessitated the development of hybrid NOMA schemes combining the merits of the individual NOMA schemes for optimal performance. The hybrid technologies on 5G networks make complex air interfaces resulting in new resource allocation (RA) and user pairing (UP) challenges aimed at limiting the multiplexed users interference. Furthermore, common analytical techniques for evaluating the performance of the schemes lead to unrealistic network performance bounds necessitating alternative schemes. This work explores the feasibility of a hybrid power domain sparse code non-orthogonal multiple access (PD-SCMA). The scheme integrates both power and code domain multiple access on an uplink network of small cell user equipments (SUEs) and macro cell user equipments (MUEs). Alternative biological RA/UP schemes; the ant colony optimization (ACO), particle swarm optimization (PSO) and a hybrid adaptive particle swarm optimization (APASO) algorithms, are proposed. The performance results indicate the developed APASO outperforming both the PSO and ACO in sum rate and energy efficiency optimization on application to the PD-SCMA based heterogeneous network.

INDEX TERMS Codewords, codebooks, NOMA, SCMA, particle swarm optimization, ant colony optimization.

I. INTRODUCTION

Non-orthogonal multiple access (NOMA) has emerged as a viable candidate for 5G access network protocols. Normally, Orthogonal multiple access (OMA) schemes have exclusivity constraints when allocating users to a resource element (RE) namely; timeslot for frequency division multiple access (FDMA), subcarrier frequency for orthogonal frequency division multiple access (OFDMA) and spreading code for code division multiple access (CDMA) based schemes. The significance of NOMA is co-multiplexing users on the same spectrum resource elements (SREs) via power domain (PD) or code domain (CD) at the transmitter and successfully separating them at the receiver by multi-user detection (MUD) schemes. This culminates in enhanced spectral efficiency when compared to conventional OMA techniques. NOMA schemes permit controllable interference by non-orthogonal resource allocation albeit increase in receiver complexity [1]. However, the multiplexing of multiple users on limited REs results in cross-tier and inter-tier interference for heterogeneous networks necessitating the development of new optimal radio resource allocation (RRA) algorithms to alleviate the user pairing problems.

Two main classes of NOMA are identified as [2]; power domain NOMA (PD-NOMA) and code domain NOMA (CD-NOMA). In PD-NOMA, different power levels based on each user's channel quality conditions are used to multiplex multiple users on the same time-frequency resources. At the receiver of PD-NOMA, users are distinguished by their power levels using successive interference cancellation (SIC). CD-NOMA is grounded on classic CDMA principles that apply sparse spreading sequences or non-orthogonal low cross-correlation sequences. In [3], multiple NOMA schemes based on low density spreading (LDS) sequences such as sparse code multiple access (SCMA), multi-user shared access (MUSA), pattern division multiple access (PDMA) are

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presented. Among various NOMA schemes SCMA exhibits improved link-level performance compared to other code domain methods [4]. In [5], the performance of two NOMA schemes (PD-NOMA and SCMA) is compared. Considering resource allocation in heterogeneous network scenarios for both multiple access (MA) techniques, SCMA is observed to outperform PD-NOMA. A joint RRA and SIC ordering algorithm is proposed for downlink power domain sparse code multiple access (PSMA) based wireless networks [6]. Matching theory and sub-modularity principles are applied to maximize sum-rate over codebook assignment. An investigation of RRA in multiple input multiple output (MIMO)-SCMA in cloud radio access networks is done in [7]. Beamforming, joint codebook allocation and user association are separately implemented to solve the developed sum-rate maximization optimization problem. To further improve the performance of the traditional NOMA schemes and optimize their performance on heterogeneous networks by combining their individual merits, hybrid schemes are required. This work proposes a hybrid NOMA scheme that integrates PD-NOMA and SCMA on the uplink of the 5G heterogeneous network called power domain SCMA (PD-SCMA). The feasibility of such a system, especially so the development of a hybrid-generalized-SIC (HG-SIC) receiver that combines both power and code diversity, the RRA schemes and the pairing of both MUEs and SUEs, on such a hybrid access technology network, is a challenging task that needs to be undertaken.

Mathematical based algorithms have been applied for resource allocation in SCMA NOMA networks [2]. There are numerous works that have solved the resource allocation (RA) problem in SCMA using analytical Lagrangian optimization based approach. This generally involves defining the Lagrange function and solving the corresponding dual problem. Lagrangian optimization can provide optimal solutions although it is mathematically rigorous. One of the challenges of Lagrangian optimization is the difficulty that arises when dealing with non-convex problems which usually requires relaxation to be transformed into convex problems leading to approximate boundary solutions. More accurate alternative methodologies are required, hence the proposal of applying biologically inspired algorithms. Biologically inspired algorithms are seldom applied for RA in NOMA, despite the fact that they can provide optimization solutions in NOMA networks. Their adaptive characteristic makes them appropriate for the constantly changing wireless network conditions. Meta-heuristic algorithms have the advantage of simple implementation once optimization solutions can be formulated into the algorithms' framework. However, it can be challenging to represent feasible solutions into meta-heuristic algorithm structures.

Ant colony optimization (ACO) [8] emulates the behaviour of ants rummaging for food in nature. During their searching expeditions ants communicate with each other using indirect communication, referred to as "stigmergy". They accomplish this by leaving *pheromone* trails for other ants to follow towards food sources. The paths generated by ants during their tours represent potential solutions to the optimization problem. ACO has an inherent parallel and positive feedback mechanism which makes it attractive for finding user multiplexing in NOMA. Random tours in the beginning of the algorithm can reduce its performance. Introduced in [9], Particle swarm optimization (PSO) is based on simple social interaction of birds. Birds often search for food as a swarm and communicate information regarding their findings within the flock to maximize their discoveries. In PSO, particles represent potential solutions to the optimization problem. Due to its simple implementation and efficiency in solving continuous problems, PSO is attractive for enabling sharing of resources in NOMA. Biological optimization algorithms can be effective in procuring solutions to non-convex problems that often arise in RA in SCMA. To our knowledge there is limited work on the application of biological optimization methods in literature for uplink SCMA NOMA RA except the work in [10].

The proposed PD-SCMA for 5G networks enables a new transmission policy that allows more than two MUEs and FUEs to be co-multiplexed over the same RE. The developed HG-SIC receiver combines both the power and diversity (patterns) gain in MUD. The scheme jointly optimizes the combinatorial problem of subchannel assignment and power allocation to maximize the overall system energy efficiency (EE) of the small cells. Power resources are chosen as the fundamental multiplexing domain between the MUEs and SUEs, and code domain as the key multiplexing domain in the sparse code multiplexing of the SUEs. The complexity of the system requires alternative RA algorithms. The work then develops alternative metaheuristic Biological RRA based on ant colony optimization and particle swarm optimization for optimizing EE resource allocation in hybrid heterogeneous networks (HetNets). The performance of this algorithms is compared to the analytical Lagrangian based approach [11], which provides upper performance bounds and can easily result in system design parameter overestimation.

The rest of the paper is organized as follows: Section II outlines related work on EE RA in SCMA and previous hybridization applications of the above mentioned algorithms. Section III describes the system model to be adopted in the paper, and Section IV shows how the EE problem is formulated. Section V develops the RA and encoding. The application of RA algorithms is outlined in Section VI with the receiver algorithm developed in Section VII.Section VIII evaluates the performance of the algorithms and Section IX concludes the paper.

II. RELATED WORK

Mathematical based resource allocation methods have been studied in previous works. Research on codebook based RA for uplink SCMA with the objective of optimizing subcarrier and power allocation to maximize total sum-rate is conducted in [2]. The derived optimization problem is solved using a matching algorithm. RA for NOMA adopting game theory approaches is presented in [12]. A user subchannel soap matching algorithm is proposed to solve the RA problem. Game theory based uplink power control (PC) in a NOMA system consisting of two interfering cells is done in [13]. A distributed PC algorithm is developed and proven to converge to the Nash equilibrium. Power minimization efforts for NOMA are done in [14]. Solutions to the considered NP-hard optimization problem are derived through relaxation and application of convex methods. Work on RA in SCMA enabling ultra reliable low latency communications is considered in [15]. With the aim of maximizing transmit rate assuming finite block-length codes, the optimization problem is solved using Lagrangian based methods and an iterative algorithm implemented. A comparison of the mathematical lagrangian based algorithms to the biologically inspired algorithms for a NOMA based HetNet has not been done in literature. Adaptive codebook design and allocation in energy saving SCMA networks is presented in [16]. Joint codebook assignment followed by power allocation is then applied. Uplink contention based SCMA for 5G networks is studied in [17]. System-level solutions are derived for UL SCMA networks in 5G radio access scenarios.

PSO application in maximizing energy efficiency subject to minimal sum-rate requirement on an uplink multi-user SCMA system is done in [10]. The non-convex EE maximization problem is solved using cooperative coevolutionary particle swarm optimization (CCPSO) algorithm. A power allocation algorithm based on PSO for application on downlink NOMA systems is developed in [18]. A fitness function is defined for energy efficiency and its performance evaluated through simulations. A PSO motivated power allocation technique for downlink NOMA IoT enabled systems is presented in [19]. The performance of the designed PSO approach is compared to conventional PA methods such as equal power allocation and water-filling. User-pairing schemes employing PSO based methods are investigated in [20]. The considered channel-aware strategies enable transmitters to minimize transmit power for multiplexed users while satisfying minimum QoS constraints for all users. A dynamic spectrum allocation method involving an enhanced PSO with mutation properties is outlined in [21]. The applied PSO is utilized to solve the non-convex power and rate optimization problem that arises. The application of PSO on NOMA based HetNets has rarely been done.

Generally, in different fields, ACO application in rate adaptive RA with proportional fairness using ACO is done in [22]. ACO is applied to solve the subcarrier allocation and sub-optimal power allocation subsequently implemented. An ACO approach to solve project scheduling problems is given in [23]. A two-pronged pheromone updating and evaluation mechanism is implemented for ants to find new solutions. In [24], parameters of an ACO algorithm are optimized in the travelling salesman problem (TSP) applications. An example of the application of hybrid ACO and PSO to optimize workflow scheduling in a cloud environment is demonstrated in [25]. The proposed method is aimed at minimizing overall workflow-time and reducing costs. A hybrid heuristic algorithm composed of PSO and ACO is conceived for task scheduling scenarios in fog computing smart production lines in [26]. The proposed technique is targeted at enhancing the energy efficiency of resource limited devices with high power consumption. Hybrid ACO based algorithms for NOMA based networks have been implemented in seldom.

For general RA in NOMA mainly on the downlink, a unified framework that examines the energy efficiency of an SCMA low complexity algorithm is investigated in [4]. Optimization of RA in dual-hop relays for multi-user SCMA is studied in [11] with a two-step joint codebook and power allocation subsequently presented. An RA strategy for SCMA based downlink system with the aim of maximizing system throughput is outlined in [27]. Proportional fair (PF) and modified largest weighted delay first algorithm (M-LWDF) are applied to solve the optimization problem. Regarding RA on the uplink, spectrum sharing between LTE and SCMA for resource allocation is conducted in [28]. Heuristic algorithms with a target of maximizing overall attainable data rate are implemented. Device-to-device (D2D) communication in uplink SCMA targeting sum-rate maximization is considered in [29]. A low-complexity two-step algorithm combining heuristic and inner approximation method is employed to solve the optimization problem. In [30], spectral efficiency in uplink SCMA considering channel state information (CSI) estimations is presented. An application of SCMA to wireless multicast communication to increase multicast capacity is done in [31]. A sub-optimal algorithm that handles power and codebook assignment separately is then proposed. Efforts to maximize sum-rate and fairness in uplink SCMA using joint channel and power are illustrated in [32]. Iterative algorithms that jointly allocate codebooks and transmit power in subcarriers are implemented with convex programming used to optimize performance. In [33], a power domain SCMA in which the power domain and code domain NOMA paradigms are combined in transmitting multiple user signals over a subcarrier on the downlink is presented. SCMA codebooks are reused by multiple users employing power domain NOMA (PD-NOMA) to transmit signals non-orthogonally. A joint power domain and SCMA downlink system is also developed in [34]. MPA combined with SIC is implemented in the receiver. A network model that applies hybrid PD-SCMA technology to a two tier HetNet uplink featuring MUEs and SUEs user pairing with cross tier interference has not been developed.

There is limited work on the application of ant colony optimization and particle swarm optimization and their hybrids in resource allocation on power domain sparse code multiple access networks. Thus, the focus of this work is to develop hybrid power domain SCMA optimization problem framework, investigate the application of metaheuristic algorithms (ACO and PSO and a developed hybrid) resource allocation, compare the performance of the proposed algorithms to the analytical Lagrangian

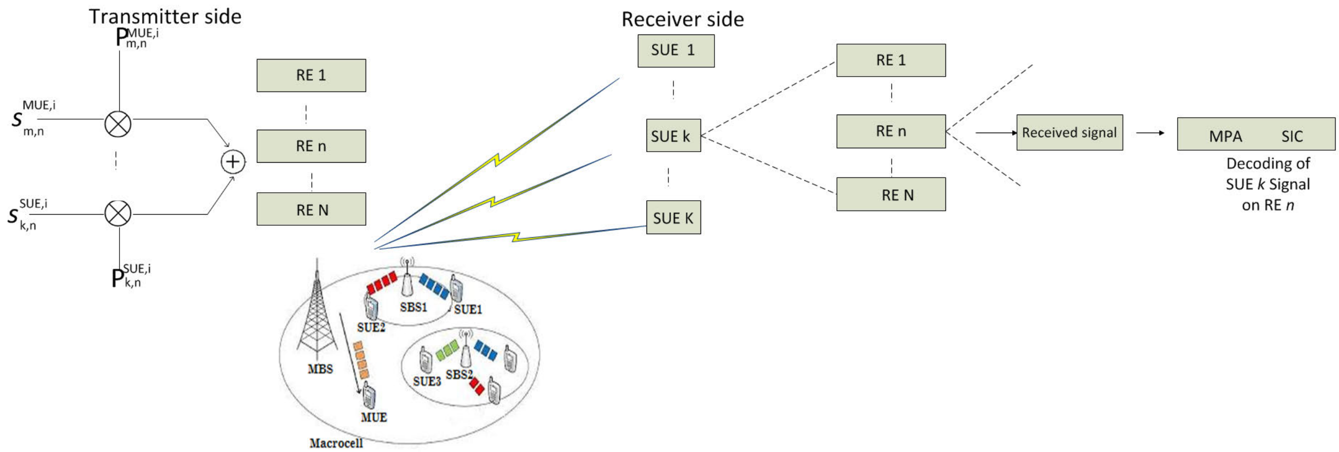

FIGURE 1. System model.

based optimization which shows possibilities of system overestimation.

III. SYSTEM MODEL

The network model is a two-tier HetNet consisting of a centralised single macro base station (MBS) uniformly populated by a set of $S_i = \{1, 2, \ldots, F\}$ centralised small cell base stations (SBSs) and M MUEs as in Figure 1. Each of the F small cells is populated with K uniformly distributed SUEs. As in [2], it is assumed an SUE is represented as an SCMA layer and each user is assigned a RE. The REs are shared among SUEs while MUEs are co-multiplexed over the same time-frequency resources using PD-NOMA. In the uplink HetNet model, REs can be reused between MUEs and SUEs in small cells as PD-NOMA is coupled with SCMA in MUE communication, while only SCMA is employed in small cells.

The network total bandwidth B, is divided into N REs occupying a bandwidth $B_{sc} = B/N$. The transmitter assigns power level, $P_{k,n}^{SUE,i}$, to the the k^{th} SUE in i^{th} SBS on the n^{th} RE and also allocates transmit power, $P_{m,n}^{MUE,i}$, to the m^{th} MUE associated with in i^{th} SBS on the n^{th} RE. Let $h_{k,n}^{SUE,i}$ and $h_{m,n}^{MUE,i}$ denote the channel gain of the k^{th} SUE to the i^{th} SBS on the n^{th} RE, and the channel gain of the m^{th} MUE on the n^{th} RE associated with the i^{th} SBS. Define $V_{K,N}^{SUE,I} = [\mu_{k,n}^{SUE,i}]_{F\times K\times N}$ as the RE HG-NOMA transmitter RE matrix for small cells where $\mu_{k,n}^{SUE,i} = 1$ implies that the k^{th} SUE connected to the i^{th} SBS has been assigned the n^{th} RE. In a similar manner, $V_{M,N}^{MUE,I}$ can also be defined such that $V_{M,N}^{MUE,I} = [\mu_{k,n}^{MUE,i}]_{M\times N}$ as the HG-NOMA RE matrix where $\mu_{k,n}^{MUE,i} = 1$ means that the n^{th} RE has been allocated to the m^{th} MUE in the i^{th} SBS. Based on the hybrid power domain SCMA paradigm following the work in [33], the received signals can be detected using MPA and SIC. This consideration allows for the reuse of REs among MUEs and SUEs.

Focusing on the small cell network, the received signal of the k^{th} SUE on the n^{th} RE in the i^{th} SBS, $y_{k,n}^{SUE,i}$, after SUEs multiplexing is expressed as

$$y_{k,n}^{SUE,i}(t) = \underbrace{V_{k,n}^{SUE,I}(\sqrt{P_{k,n}^{SUE,i}}h_{k,n}^{SUE,i}s_{k,n}^{SUE,i})}_{\text{Desired signal}} + \underbrace{\sum_{j\neq k}^{K} V_{j,n}^{SUE,I}(\sqrt{P_{j,n}^{SUE,i}}h_{j,n}^{SUE,i}s_{j,n}^{SUE,i})}_{I_{k,n}} + \underbrace{\sum_{m=1}^{M} V_{m,n}^{MUE,I}(\sqrt{P_{m,n}^{MUE,i}}h_{m,n}^{MUE,i}s_{m,n}^{MUE,i}) + w_{i,k,n}}_{I_{CT}}, \tag{1}$$

where $s_{k,n}^{SUE,i}$ is the k^{th} SUE message symbol on the n^{th} RE in i^th SBS, $s_{m,n}^{MUE,i}$ is the message symbol of the m^{th} MUE on the n^{th} RE affiliated with the i^{th} SBS. $I_{k,n}$ is the intra-tier interference and I_{CT} denotes the cross-tier interference from the M MUEs. $w_{i,k,n}$ is the noise vector modelled as Additive Gaussian White Noise (AGWN). The RE matrices $V_{K,N}^{SUE,I}$ and $V_{K,N}^{MUE,I}$ are determined in Section V. It is assumed that each base station has perfect knowledge of channel state information (CSI).

IV. PROBLEM FORMULATION

The signal to noise-plus interference (SINR) of k^{th} SUE in i^{th} SBS using n^{th} RE, $\Gamma_{k,n}^{SUE,i}$, is given by

$$\Gamma_{k,n}^{SUE,i} = \frac{V_{k,n}^{SUE,I}P_{k,n}^{SUE,i}|h_{k,n}^{SUE,i}|^2}{I_{k,n} + I_{CT} + E\{|\sigma|^2\}}, \tag{2}$$

where σ^2 is the additive white gaussian noise (AWGN). The upper bound of the attainable sum rate of each user can be expressed as

$$R_{k,n}^{SUE,i} = log_2(1 + \Gamma_{k,n}^{SUE,i}). \tag{3}$$

The total rate of the system can be expressed as

$$R_{tot} = \sum_{i=1}^{F}\sum_{n=1}^{N}\sum_{k=1}^{K} \mu_{k,n}^{SUE,i} log_2(1+\Gamma_{k,n}^{SUE,i}), \tag{4}$$

The total power,P_{tot}, consumed by the system can be written as

$$P_{tot} = \sum_{i=1}^{F}\sum_{k=1}^{K}\sum_{n=1}^{N} P_{k,n}^{SUE,i} + KP_{sta}, \tag{5}$$

where P_{sta} is the SUEs static power. The energy efficiency, η_e, of the system is defined as [10]

$$\eta_e = \frac{R_{tot}}{P_{tot}}. \tag{6}$$

Therefore, the energy efficiency optimization problem considering minimum rate requirements can be formulated as

$$\max_{V_{k,n}^{SUE,I}, P_{k,n}^{SUE,i} \geq 0} \{\eta_e(R_{tot}, P_{tot})\}, \tag{7}$$

subject to:

$$C1: \sum_{i=1}^{F}\sum_{k}^{K}\sum_{n=1}^{N} \mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} \geq R_{k,n}^{min},$$

$$C2: \sum_{n=1}^{N} \mu_{k,n}^{SUE,i} P_{k,n}^{SUE,i} \leq P_{max},$$

$$C3: P_{k,n}^{SUE,i} \geq 0,$$

$$C4: \sum_{i=1}^{K} \mu_{k,n}^{SUE,i} + \sum_{i=1}^{M} \mu_{k,n}^{MUE,i} \leq d_f,$$

$$C5: \sum_{i=1}^{K} \mu_{k,n}^{SUE,i} + \sum_{i=1}^{M} \mu_{k,n}^{MUE,i} \leq d_s,$$

$$C6: \mu_{k,n}^{SUE,i} or \mu_{k,n}^{MUE,i} \in \{0, 1\},$$

$R_{k,n}^{min}$ in $C1$ is the minimum system sum-rate required for the SUEs, P_{max} in $C2$ is the maximum transmit power of SUEs, d_f in $C4$ is the degree of RE which means that a RE can be used at most by d_f users, $C5$ implies that the maximum number of REs utilized by each user is d_s, set to $d_s = 3$ in this work to minimize receiver complexity.

V. RESOURCE ALLOCATION AND ENCODING

A. POWER ALLOCATION

To allocate power to SUEs, a well established method of water-filling [35] is adopted due to its simple implementation. Assuming initial minimum power allocation level, let $\{\tilde{h}_{k,n}^{SUE,i}\}$ be a sorted sequence of channel gains which is positive and monotonically decreasing. Define d_i as the step depth written as $d_i = \frac{1}{\tilde{h}_{k,n}^{SUE,i}}$, for $i = 1, 2, \ldots, N$, where N is the number of channels. Then the step depth difference, $\delta_{i,j}$, can be expressed as

$$\delta_{i,j} = d_i - d_j = \frac{1}{\tilde{h}_{k,n}^{SUE,i}} - \frac{1}{\tilde{h}_{k,n}^{SUE,j}} (1 \leq i, j \leq N), \tag{8}$$

The power allocation vector level, $P_{k,n}^{SUE,i}$, can be obtained using [35]

$$P_{k,n}^{SUE,i} = \left\{P_{max} - \sum_{i}^{N-1} \delta_{i,j}\right\}^{+}. \tag{9}$$

The implemented power allocation is shown in Algorithm 1.

Algorithm 1 Water-Filling Based Power Allocation

```
Input: N, P_max
Output: P = {P_{k,n}^{SUE,i} | ∀i ∈ N}
Initialize minimum power allocation, P_{k,n}^{SUE,i}, across REs
for i=1:F do
    for k=1:K do
        for n=1:N do
            Sort SUEs based on their channel
            conditions, equation (2)
            Update power allocation vector P using
            equation (8), (9)
        end
    end
    Continue process until convergence reached or
    number of iterations exceeded.
end
```

B. SCMA ENCODING

The encoding where REs are mapped to a set of C codebooks with the number of codebooks that can be generated determined as $C = \binom{L}{J}$ is used [3], [33]. The SCMA encoding process in which $log_2 Q$ binary bits are mapped to L-dimensional codewords of size Q is illustrated in Figure 2. Each codebook is assumed to contain Q codewords with length L which are transmitted over orthogonal radio resources (such as OFDMA subcarriers). The L-dimensional codewords that constitute a codebook are sparse vectors with J non-zero entries where $J < L$. In this scenario, the overloading factor can be defined as $\lambda = K/L$. For the k^{th} SUE on the n^{th} RE in i^{th} small cell ($SUE_{k,n}^{i}$), and the m^{th} macro cell user on n^{th} RE in the proximity of i^{th} small cell ($MUE_{m,n}^{i}$), a codebook is allocated with codebook reuse being allowed as in [33]. As codebooks are transmitted on different wireless channels, the MPA receiver can still recover the data streams without collisions. Codebook reuse can improve both the overloading factor and the number of connections to enable massive connectivity. Optimal SCMA decoding is achieved using the maximum a priori (MAP) decoding [36] but the message passing algorithm (MPA) which offers approximate performance at reduced decoding complexity is considered in this work.

C. RESOURCE ALLOCATION

Consider the scenario where the k^{th} user is allocated a maximum of d_s REs (equation 7 $C5$). Let the UE-to-RE

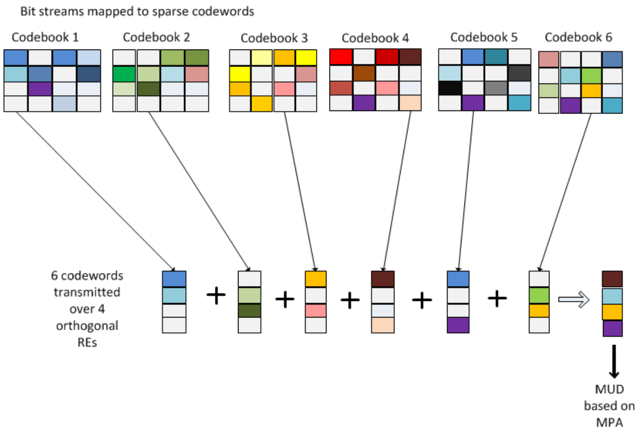

FIGURE 2. **Example of SCMA encoding with K = 6 SUEs,L = 4 REs, J = 2.**

matrix, A_k, be a $N \times d_s$ matrix where rows represent REs in the system. To preserve the sparsity of SCMA, there is only one non-zero entry in each column of A_k which corresponds to the RE designated to the k^{th} user. For instance, if $d_s = 2$, $N = 4$, and user 1 is allocated the first and third REs, its spreading matrix could be expressed as

$$A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}. \tag{10}$$

For K users in the system, the corresponding SCMA spreading matrix of size $N \times (Kd_(s))$ is given by

$$A_k^N = [A_1, A_2, \dots, A_K]. \tag{11}$$

In (11), the columns are derived in the following manner. The columns belonging to the k^{th} user are in the range $(k-1)d_s+1$ to kd_s. For example, an SCMA system with $K = 6$, $N = 4$, $d_s = 2$ operating at full-load could have the following spreading matrix,

$$A_N^K = \begin{bmatrix} 1&0&0&0&1&0&0&0&0&0&1&0 \\ 0&0&1&0&0&1&0&0&1&0&0&0 \\ 0&1&0&0&0&0&1&0&0&1&0&0 \\ 0&0&0&1&0&0&0&1&0&0&0&1 \end{bmatrix}. \tag{12}$$

Having derived the spreading matrix in (12) UE-RE correlation can be encapsulated in a factor matrix defined as $F_k^n = [f_1, f_2, \dots, f_K]$, where $f_k^n = 1$ implies that k^{th} UE occupies n^{th} resource element and $f_k^n = 0$ means no resources have been assigned. The elements of the factor matrix are computed from $f_k = diag(A_k A_k^T)$. Consequently, the factor matrix for the previous example in (12) is given by

$$F_k^n = \begin{bmatrix} 1&0&1&0&0&1 \\ 0&1&1&0&1&0 \\ 1&0&0&1&1&0 \\ 0&1&0&1&0&1 \end{bmatrix}. \tag{13}$$

The first column of F_k^n represent the first UE is allocated the first and third REs. Similarly, the second UE is assigned the second and fourth REs as shown in the second column of F_k^n, and the rest of the UEs are assigned as illustrated in the remaining columns of F_k^n. The first row represents the first RE which is utilized by the first, third and sixth UEs. The UE-RE scheduling vector, V_{sc}^n, can be succinctly written as

$$V_{sc}^n[RE] \Leftrightarrow [UE_1, UE_2, \dots, UE_K], \tag{14}$$

where UE_k is allocated a set of d_s REs based on the root mean square (RMS) values of the channel gains. Note that the RA matrices $V_{k,n}^{SUE,I}$ and $V_{k,n}^{MUE,I}$ of Section III are a subsets of $V_{sc}^n[RE]$.

VI. APPLICATION OF RA ALGORITHMS

The conventional application of the lagrangian method in optimization of (7) is as in [37]. In the alternative algorithms, user to RE pairing is performed using biological algorithms based on channel conditions. At the beginning of the RA process, the biological algorithms embark on a random search for UE to RE pairs based on SINR conditions. The random explorations are utilized to initialize the algorithms in their respective frameworks. Considering the constantly changing wireless channel conditions, the adaptive nature of the biological algorithms is exploited to discover channels in which UEs have better SINR so as to maximize the data rate at minimum transmit power.

A. LAGRANGIAN BASED OPTIMIZATION

The optimization problem in (7) is a non-convex problem that needs to be transformed using nonlinear fractional programming Dinkelbach approach [37] before it can be solved using convex based techniques such as Lagrangian optimization. The optimization problem in (7) can be re-written as

$$\max_{\mu_{k,n}^{SUE,i}, P_{k,n}^{SUE,i} \geq 0} \{R_{tot} - \eta_e(P_{tot})\}, \tag{15}$$

It can be proven that the optimal solution of the subtractive form of the optimization problem in (15) is reached when $R_{tot} - \eta_e(P_{tot})\}$ approaches zero. If the objective function in (7) has undergone transformation to reduce the non-convex complexity by assuming the binary variable $\mu_{k,n}^{SUE,i}$ to be continuous, then the Lagrangian function can be expressed as

$$\begin{aligned} &L(R, P, \eta_e, \Omega) \\ &\quad = R_{tot} - \eta_e(P_{tot})\} \\ &\qquad -\lambda(\sum_{n=1}^{N} \mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} - R_{k,n}^{min}) - \gamma(\sum_{j=1}^{J} \mu_{k,n}^{SUE,i} - d_f) \\ &\qquad -\alpha(\sum_{k=1}^{K} \mu_{k,n}^{SUE,i} - d_s) - \beta(P_{max} - \sum_{n=1}^{N} \mu_{k,n}^{SUE,i} P_{k,n}^{SUE,i}), \end{aligned} \tag{16}$$

where $\Omega = (\lambda \geq 0, \gamma \geq 0, \alpha \geq 0, \beta \geq 0)$ are Lagrange multipliers for relaxed constraints. Constraints in $C3$ and $C6$ are absorbed by Karush-Kuhn-Tucker (KKT) conditions.

The dual function can be defined as

$$g(\eta_e, \Omega) = \max_{R_{k,n}^{SUE,i}, P_{k,n}^{SUE,i}} L(P, R, \eta_e, \Omega), \tag{17}$$

The dual problem can correspondingly be expressed as

$$\min_{R_{k,n}^{SUE,i}, P_{k,n}^{SUE,i}} g(\eta_e, \Omega), \tag{18}$$

In solving the Lagrangian function, (16) is decomposed into a master problem and $K \times N$ subproblems. The solution of each subproblem is derived by iteratively solving the subproblem in the corresponding SBS. The equation in (16) can be written as

$$L_(R, P, \eta_e, \Omega) = L_{in} + \lambda(R_{k,n}^{min}) - \gamma(d_f) - \alpha(d_s) - \beta(P_{max}), \tag{19}$$

where

$$L_{in} = \sum_{n=1}^{N} \mu_{k,n}^{SUE,i} R_{k,n}^{SUE,i} + \sum_{k=1}^{K} \eta_e P_{k,n}^{SUE,i} \\ -\lambda(R_{k,}^{SUE,i}) - \gamma d_f - \alpha(d_s) - \beta(P_{k,n}^{SUE,i}). \tag{20}$$

Optimal transmit power is obtained by applying KKT conditions in combination with optimization methods,

$$P_{k,n}^{SUE,i} = \frac{B_{sc}(1+\gamma)}{\sum_{j\neq k}^{K} B_{sc}(1+\gamma)(\Gamma_{j,n}^{SUE,i}) + ln2(\lambda + \chi_{k,n}^{MUE,i})}, \tag{21}$$

where $\chi_{k,n}^{MUE,i} = \mu_{k,n}^{MUE,i} h_{k,n}^{MUE,i}$. The subgradient method is employed to update Lagrangian dual variables as follows

$$\lambda^{t+1} = \lambda^t - \zeta_1^t \left[R_{k,n}^{SUE,i} - R_{k,n}^{min} \right]^+, \tag{22}$$

$$\beta^{t+1} = \beta^t - \zeta_2^t \left[P_{max} - \sum_{n=1}^{N} \mu_{i,k,n} P_{k,n}^{SUE,i} \right]^+, \tag{23}$$

where ζ_1^t and ζ_2^t are step sizes of iteration $t \in \{1, 2, \ldots, I_{max}\}$. When the step sizes are sufficiently small, the Lagragian multipliers converge to equilibrium points. The implemented scheduling algorithm is as outlined in Algorithm 2.

Algorithm 2 Lagrangian PD-SCMA Resource Scheduling

```
Input: Maximum number of iterations, I_max
Initialize maximum number of iterations I_max Initialize
  energy efficiency η_e and equal power allocation, P_{k,n}^{SUE,i}
  across REs
while (convergence not reached or maximum iterations
  exceeded) do
    for i=1:F do
        for n =1:N do
            Initialize Lagrange multipliers (λ, γ, α, β)
            Given η_e, compute P_{k,n}^{SUE,i} equation (21 ),
            Update available resources, equation (7)
            (C5&C6),
            Determine the throughput, equation (4),
            Update Lagrange multipliers according
            to (22), (23),
            Continue process until convergence reached
            or number of iterations exceeded.
        end
    end
end
```

B. PARTICLE SWARM Optimization(PSO)

1) PRINCIPLE OF OPERATION

In the basic PSO [9], a particle represents a viable solution to the objective function $F(x)$ where x is the decision vector in D dimensional search space. The i^{th} particle position in the search space can be expressed as a position vector $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ which roves in the search space with velocity $v_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]$. As particles traverse the search space, a fitness function (f) related to $F(x)$ is evaluated for each particle and the positions of highest personal fitness values of particles, f_{pbest}, and the best fitness value of the entire swarm, f_{gbest}, are stored. Given a swarm of P_n particles, with the personal best values, $P_{i,f_{pbest}}$, and global best value, $P_{i,f_{gbest}}$, of the particles can be expressed as

$$P_{i,f_{pbest}} = arg \quad min[f_{pbest}, x_{id}], \tag{24}$$

$$P_{i,f_{gbest}} = arg \quad min[f_{gbest}, x_{id}], \tag{25}$$

Particles instantaneously update their velocity vector to attain their previous best fitness and migrate towards the swarm's global best fitness value. Each i^{th} particle's d^{th} dimension has velocity, v_{id}^{t+1}, calculated according to

$$v_{id}^{t+1} = wv_{id}^t + c_1 r_1 (P_{i,f_{pbest}} - x_{id}^t) + c_2 r_2 (P_{i,f_{gbest}} - x_{id}^t), \tag{26}$$

where w is particles inertia, $P_{i,f_{pbest}}$ is the personal best position of the particle, c_1 and c_2 are personal and social learning factors respectively. The variables r_1 and r_2 are random values normally in the range 0 to 1. Particles' d^{th} dimension position is updated as

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}, \tag{27}$$

where v_{id} is the velocity vector with an equivalent dimension as the position vector. The dimensions of the search space varies based on the nature of the optimization problem under consideration. Information pertaining to particles' current positions and their personal bests is stored in matrices X_p and Y_p respectively.

$$X_p = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,F} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,F} \\ \vdots & \vdots & \ddots & \vdots \\ x_{sk,1} & x_{sk,2} & \cdots & x_{sk,F} \end{bmatrix}, \tag{28}$$

$$Y_p = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,F} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,F} \\ \vdots & \vdots & \ddots & \vdots \\ y_{sk,1} & y_{sk,2} & \cdots & y_{sk,F} \end{bmatrix}. \tag{29}$$

The i^{th} row of X_p is a F-dimensional vector concatenating all current position vectors x_i from K particles.

2) PSO RE SCHEDULING

In application of PSO to SCMA RA, particles represent feasible solutions to the RE scheduling optimization problem which involves codebooks assignment to users. The fitness function, $F(x)$, is the energy efficiency optimization problem of equation (7) expressed as

$$F(x) \Leftrightarrow max\{\eta_e(R,P)\}. \tag{30}$$

As particles traverse the search space to discover UE-RE assignments which yield good energy efficiency solutions, they evaluate the fitness function of equation (30). A particle in this instance represents the multiplexing of K SUEs using L-dimensional codewords over N subcarriers to solve the optimization problem of equation (7) with the associated constraints. In every Transmission Time Interval (TTI), the position of each particle, x_{id} represents a feasible RE assignment and is constructed to form the resource scheduling vector defined as a position vector $x_{id} = [x_{i1}, x_{i2}, \ldots, x_{iN}]$,

$$x_{id} \Leftrightarrow V_{sc}^{n}[RE], \tag{31}$$

where $V_{sc}^{n}[RE]$ is given by equation (14). Particles then update their personal best positions which corresponds to the best scheduling solution the particle has discovered thus far. The global best particle position is updated if the personal best of the particle at that instant is detected to be better than the current global best position. The implemented scheduling algorithm is outlined in Algorithm 3.

Algorithm 3 PSO PD-SCMA Resource Scheduling

Input:
UEs: $U = \{\ 1,\ldots,\text{k},\ldots,UE_K\ \}$
REs: $R = \{1,\ldots,\text{n},\ldots RE_N\ \}$
Initialize: c_1, c_2, r_1, r_2, w
while *(convergence not reached)* **do**
  for *i=1:F* **do**
    for *n =1:N* **do**
      Generate random positions of particles and store them, equation (27) & (28).
      Perform RA, equation (14),
      Update available resources, equation (7) $(C5\&C6)$,
      Determine the throughput, equation (4),
      Allocate power, Algorithm 1,
      Evaluate particle fitness, equation (30),
      Update,f_{pbest}, equation (24)& (29),
      if $P_{i,f_{gbest}} > P_{i,f_{gbest}}$ **then**
        Update, $P_{i,f_{gbest}}$, equation (25),
      end
      Allocate power, Algorithm 1,
      Continue process until convergence is reached or number of iterations exceeded.
    end
  end
end

C. ANT COLONY OPTIMIZATION (ACO)

1) PRINCIPLE OF OPERATION

A typical ACO application involves modelling a discrete combinatorial optimization problem as a construction graph. The optimization problem is formulated as a graph coloring problem represented by $G = (V, E)$ where V is the number of vertices and E is the number of edges. In the Ant Colony Optimization Assignment Type Problem (ACO ATP) [38], [39], i nodes are assigned j colors where items are assumed to be nodes on the graph and objects are represented by colors. Artificial ants generate paths which are feasible solutions as they travel through the graph. In each path, ants choose a path $P_{i,j}$ which represents an assignment of j objects to i items, and evaluate the fitness function $F_{i,j}(x)$ which is related to the objective function being optimized.

$$P_{i,j} = max\{F_{i,j}(x)\ \}. \tag{32}$$

They choose the optimal path, $P_{i,j}^{op}$, that maximizes the fitness function F_{ij}^{op},

$$P_{i,j}^{op} = max\{F_{i,j}^{op}(x)\ \}. \tag{33}$$

An ATP ACO set up often requires two probabilistic rules for choosing nodes and colors. The first probability, $p'_{i,j}(t)$, for ant a choosing the next node when it is at node i, is given by

$$p'_{i,j}(t) = \frac{\tau_{i,j}^{'\alpha}(t)\eta_{i,j}^{'\beta}(t)}{\sum_{j\in S_i^k(t)} \tau_{i,j}^{'\alpha}(t)\eta_{i,j}^{'\beta}(t)}, \tag{34}$$

where α, β are pheromone weighting factors, $\tau'_{i,j}$, is the pheromone intensity, $\eta'_{i,j}$ is the desirability, and $S_i^k(t)$ is set of feasible nodes from ant a at node i. The desirability of ant a choosing the next node is given by the heuristic function, $\eta'_{i,j}(t)$,

$$\eta'_{i,j}(t) = \frac{1 + |N_{unassigned}^{k}|}{1 + |N_{nei,i}|}, \tag{35}$$

where $|N_{unassigned}^{k}|$ is the number of neighbours to the current node that have not been allocated objects, and $|N_{nei,i}|$ is the number of neighbors from the perspective of the ant when at node i. The pheromone in previously chosen nodes is defined as

$$\tau'_{i,j}(t) = \frac{F_{i,j}^{best}}{|N_i^{best}(t)|}, \tag{36}$$

where $F_{i,j}^{best}$ is the fitness function of best ant, and N_i^{best} is the set of feasible nodes from the perspective of best ant at node i. The second probability, $p''_{i,o}(t)$, of choosing an object to assign for the current node from the set of objects, N_o, is given by

$$p''_{i,o}(t) = \frac{\tau''^{\alpha}_{i,c}(t)\eta''^{\beta}_{i,o}(t)}{\sum_{j\in N_o}\tau''^{\alpha}_{i,c}(t)\eta''^{\beta}_{i,o}(t)}, \tag{37}$$

where the heuristic function, $\eta''_{i,o}$, is defined as

$$\eta''_{i,o}(t) = \frac{1 + n_{previous-best}}{1 + n_{available-obj}}, \tag{38}$$

where $n_{previous-best}$ is the number of elements in the set of previously assigned objects, $n_{available-obj}$ is the number of objects available for allocation. The pheromone, $\tau''_{i,c}$, is updated using

$$\tau''_{i,c}(t) = \frac{n_{previous-best}}{|N_i^{Best}(t)|}. \tag{39}$$

The fitness function $F_{i,j}$ of each path which represents a solution to the optimization problem is calculated along each path and paths with higher fitness have more pheromones deposited on them.

2) ANT COLONY OPTIMIZATION(ACO) RA SCHEDULING

On application to SCMA RA, UEs are represented by nodes and RE allocation patterns are associated with colors. A path that represents the assignment of n REs to k UEs can be formulated from equation (14) as

$$P_{k,n} \Leftrightarrow V_{sc}^{n}[RE]. \tag{40}$$

The optimal path, $P_{k,n}^{op}$, that maximizes optimization function is

$$P_{k,n}^{op} \Leftrightarrow \widetilde{V_{sc}^{n}}[RE] \Leftrightarrow max\{F_{k,n}(x)\}. \tag{41}$$

The fitness function, $F_{k,n}(x)$ is given by

$$F_{k,n} = max\{\eta_e(R,P)\}. \tag{42}$$

As ants traverse the search space they leave pheromone in paths that have higher fitness, i.e. RE allocations that have desirable energy efficient transmission rates in their path for other ants to follow in future travels. A colony of RA scheduling decisions is build by ants based on tours in which they discovered optimal sum rates. The applied ACO SCMA resource scheduling algorithm is summarized in Algorithm 4.

Algorithm 4 ACO PD-SCMA Resource Scheduling

```
Input:
UEs: U = { 1,...,k,...,UE_K }
REs: R = {1,...,n,...RE_N }
Initialize: α, β, ρ
while ( convergence not reached) do
    for i=1:F do
        for k=1:K do
            for n =1:N do
                Begin ant search for REs in R that satisfy
                (7, C1).
                Perform RA, equation (14),
                Update available resources, equation 7
                (C5&C6).
                Determine the throughput, equation (4)
                Allocate power, Algorithm 1,
                Evaluate fitness function, equation (41).
                Update pheromone for higher fitness
                functions, equation (36) & (39).
                Continue process until convergence
                reached or number of iterations
                exceeded.
            end
        end
    end
end
```

D. ADAPTIVE PARTICLE ANT SWARM OPTIMIZATION (APASO)

1) PRINCIPLE OF OPERATION

Artificial *ant particles* possessing both attributes of PSO and ACO are created and randomly initialized in the search space. For all ant particles the fitness function $F(x)$ is computed. To improve the performance of PSO a pheromone-guided mechanism is employed to indicate ant particles with more fitness. In [40], it is outlined how the inertia weight provides a balance between exploration and exploitation. Having a higher inertia weight in the beginning enables global search, while a lower inertia weight in later stages of algorithm enhances convergence towards personal and global best values. In our proposed APASO we consider the modification of ant particles inertia weight as

$$w \Leftrightarrow \tau_{inter}, \tag{43}$$

where τ_{inter} is the inter ant particle pheromone given by

$$\tau_{inter} = \zeta\left(\left|\frac{min(F^t_{pbest}(x), \overline{F}_t(x))}{max(F^t_{pbest}(x), \overline{F}_t(x))}\right|\right), \tag{44}$$

where ζ is a control parameter in the range [0,1], and $\overline{F}_t(x)$ is the mean fitness of all ant particles at t, and $F^t_{pbest}(x)$ is personal best fitness of ant particles at t. For a d-dimensional space, an ant particle has velocity, v_{id}^{t+1} and position, x_{id}^t, defined by

$$v_{id}^{t+1} = \tau_{inter}v_{id}^t + c_1r_1(p^t_{pb} - x^t_{id}) + c_2r_2(p^t_{gb} - x^t_{id}), \tag{45}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \tag{46}$$

where p^t_{pb} and p^t_{gb} are personal best and global best of ant particles defined similar to equations (24) and (25) respectively. In equation (45) applying the inter ant particle (τ_{inter}) pheromone to the first term on the right hand side of the equation enables diversity of ant particles' search in early iterations of the algorithm while increasing convergence in later iterations.

2) ADAPTIVE PARTICLE ANT SWARM OPTIMIZATION (APASO) SCHEDULING

The proposed hybrid technique aims to exploit advantages of PSO and ACO to attain superior performance to the conventional algorithms. In the beginning stage of the scheduling process, PSO generates new random particle ants, and the ACO based pheromone mechanism generates pheromones for ant particles to mark solutions with higher fitness values. It is these favourable qualities of the PSO and ACO that have motivated the hybridization of PSO and ACO in the proposed APASO. The position of an ant particle is modelled as scheduling vector in a particular TTI as

$$x_{id} \Leftrightarrow V_{sc}^{n}[RE], \tag{47}$$

where $V_{sc}^{n}[RE]$ is defined as equation (14). The fitness function is formulated to solve the optimization problem in equation (7) as

$$F(x) \Leftrightarrow max\{\eta_e(R, P)\}. \tag{48}$$

Each ant particle then stores its position together with its fitness value, and keeps updating velocity in equation (45) so that the ant particles maintain their migration towards better solutions. The mechanics of the APASO algorithm for RE scheduling in SCMA is summarized in Algorithm 5.

Algorithm 5 APASO PD-SCMA Resource Scheduling

```
Input:
UEs: U = { 1, ..., k, ..., UE_K }
REs: R = {1, ..., n, ... RE_N }
Initialize c_1, c_2, r_1, r_2, w, τ_inter while (convergence not
reached) do
    for i=1:F do
        for n=1:N do
            Initialize random ant particles search,
            Allocate resources, equation (14),
            Determine the throughput, equation (4),
            Distribute pheromone τ_inter, equation (44),
            Evaluate fitness function for all ant particles,
            equation (48),
            Update the velocity and position vectors for
            ant particles, equations (45) & (46),
            Update pheromone, equation (44),
            Allocate power, Algorithm 1,
            Continue process until convergence is
            reached or number of iterations exceeded.
        end
    end
end
```

VII. RECEIVER ALGORITHM AND COMPLEXITY

To detect and decode the received signal, the k^{th} SUE at i^{th} SBS using codebook c detects and removes signals of $d_f - 1$ users. Denoting the mean channel gains of users superimposed on codebook c as $\tilde{H}_{k,c}^{SUE,i}$, the receiver algorithm is outlined in Algorithm 6.

Algorithm 6 PD-SCMA Based Receiver

Input:

Received signal from all orthogonal subcarriers, Channel gain matrix for all users, $\tilde{H}_{k,c}^{SUE,i}$

Initialize maximum number of iterations I_{max}

Set $\tilde{H}_{k,n}^{SUE,i} = \min \tilde{H}_{k,c}^{SUE,i}$

Apply MPA on the received signal

Output $V_{k,n}^{SUE,I}(\sqrt{P_{k,b}^{SUE,i}} h_{k,n}^{SUE,i} x_{k,n}^{SUE,i})$ (SUE k signal on codebook n in i^{th} SBS).

Apply SIC on resulting signal

$y_{k,n}^{SUE,i} = y_{k,n}^{SUE,i} - (V_{k,n}^{SUE,I}(\sqrt{P_{k,b}^{SUE,i}} h_{k,n}^{SUE,i} x_{k,n}^{SUE,i})$

Set $\tilde{H}_{k,c}^{SUE,i} = \tilde{H}_{k,c}^{SUE,i} - \tilde{H}_{k,n}^{SUE,i}$

Repeat process until all SUEs data has been decoded.

Assume that a codebook in PD-SCMA is allocated to d_f users at the same time with each SUE applying MPA d_f times and implementing SIC (d_f-1) times in the process of detecting and decoding transmitted data. In the case where C codebooks are assigned to d_f SUEs, the complexity of the receiver can be approximated as

$$\mathcal{O}(I_{max}|\nu|^p(C)(d_f)), \tag{49}$$

where ν is the codebook size, I_{max} is the maximum number of iterations, p is the non-zero elements of factor matrix $F_k^n = f_1, \ldots, f_n$.

VIII. PERFORMANCE EVALUATION

In simulations, it is assumed that SUEs are randomly distributed in small cells which are uniformly distributed in the macrocell coverage area. The radii of the macrocell and small cells are 500m and 20m respectively, and minimum distance between the small cells and MBS is 40m. The system bandwidth is considered to be 10 MHz with the channel model assumed to characterized by small scale Rayleigh fading with large scale path loss and 8dB log-normal shadowing. The maximum transmit power is 21 dBm and P_{sta} = 18 dBm. The minimum data rate is assumed to be 5 Mbps.

Figure 3 shows a plot of sum-rate vs number of users in the network. As the number of users increases the sum-rate of the system increases, although the gradient of the sum-rate curve decreases with increasing number of users. APASO offers better performance than the PSO and ACO achieving performance close to the analytical Lagrangian. Figure 4 illustrates the variation of the sum-rate of the system vs total transmit power of users. As the transmit power is increased the sum-rate of the system increases until a saturation point is reached beyond which further transmit power increases do not yield increased sum-rate capacity of the system.

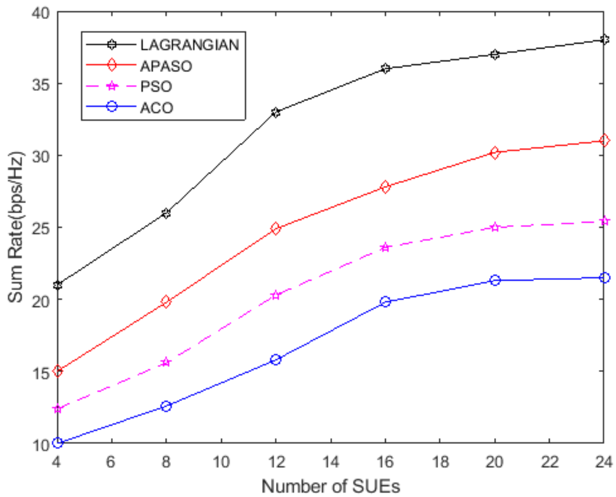

FIGURE 3. Sum-rate vs Number of users.

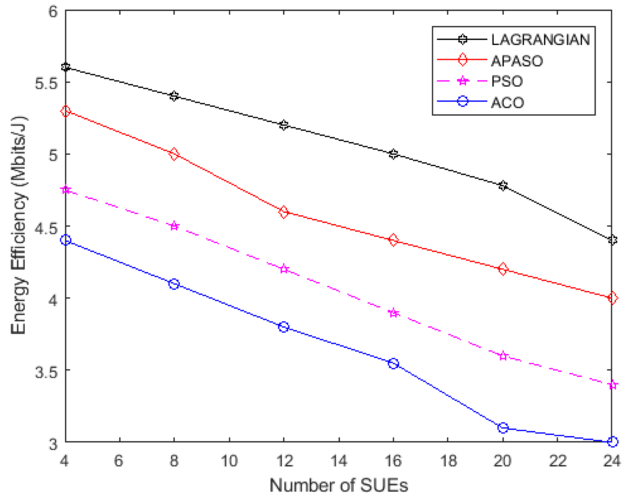

FIGURE 5. Energy efficiency vs Number of users.

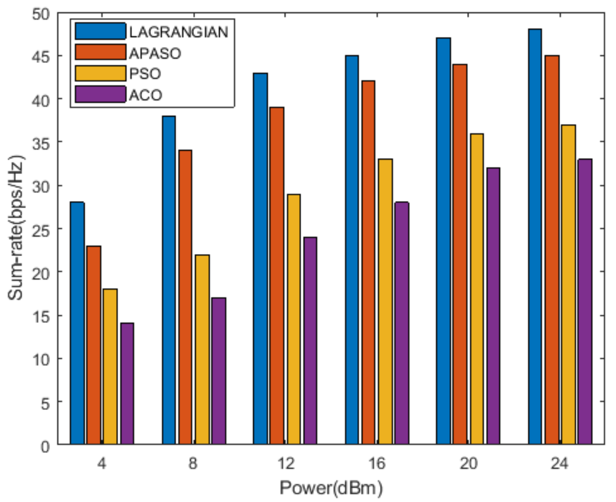

FIGURE 4. Sum-rate vs Total Power.

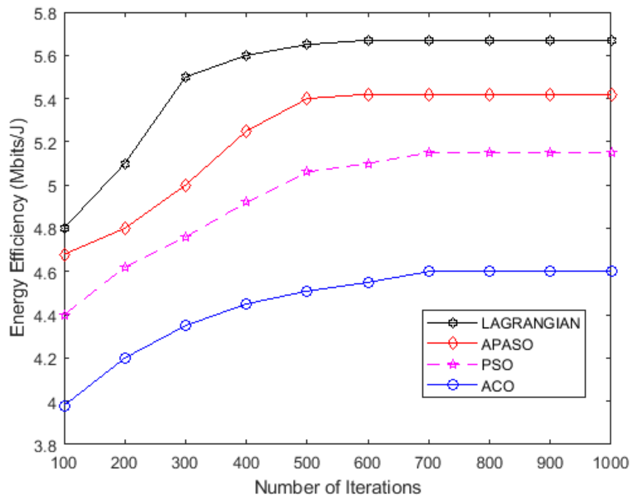

FIGURE 6. Energy efficiency vs Number of iterations.

The developed APASO outperforms the other biological algorithms, with the Lagrangian providing an upper bound. The performance of the Lagrangian in figures 3 and 4 is similar to that demonstrated in [33].

In figure 5, it is noted that as the number of users increases the energy efficiency of the systems decreases. Although the EE is higher in the beginning, it starts deteriorating with additional users in the system indicating that after the system has reached saturation, increasing number of users compromises the performance of the system. The performance of the algorithms follows a similar trend from Lagrangian to ACO.

In figure 6, the EE of the algorithms is recorded as they are executed. The developed APASO achieves higher EE and saturates faster than the other conventional biological algorithms. The pheromone mechanism adopted in APASO enhances its ability to find higher fitness ant particle solutions with higher EE. To evaluate the fairness of the algorithms in distributing resources among users in the network, Jain's fairness metric is embraced. It is defined as in [32] which can be expressed as

$$J = \frac{\left(\sum_{k=1}^{K} R_{k,n}^{FUE,i}\right)^2}{K \times \sum_{k=1}^{K} (R_{k,n}^{FUE,i})^2}. \tag{50}$$

In (50), the index has a range of $1/J$ (no fairness) to 1(perfect fairness). In Figure 7, the fairness performance of the considered algorithms is outlined. The ACO is observed to outperform other algorithms in terms of fairness as it has higher fairness index overall. This implies that the 'colony' of solutions derived using pheromone mechanism enables it to share resources more fairly among users albeit at the expense of maximizing the sum-rate. Its performance is followed by PSO and APASO with

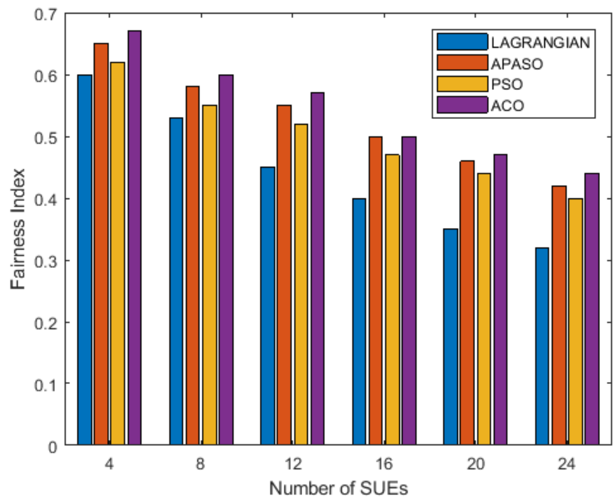

FIGURE 7. Fairness vs Number of users.

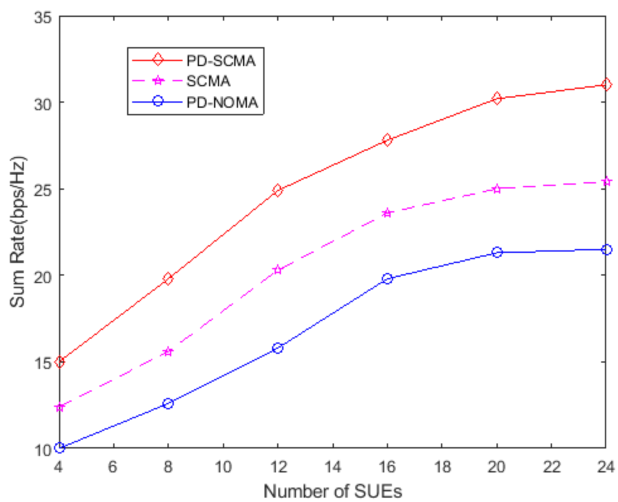

FIGURE 8. Sum-rate vs Number of users for different MA schemes using APASO.

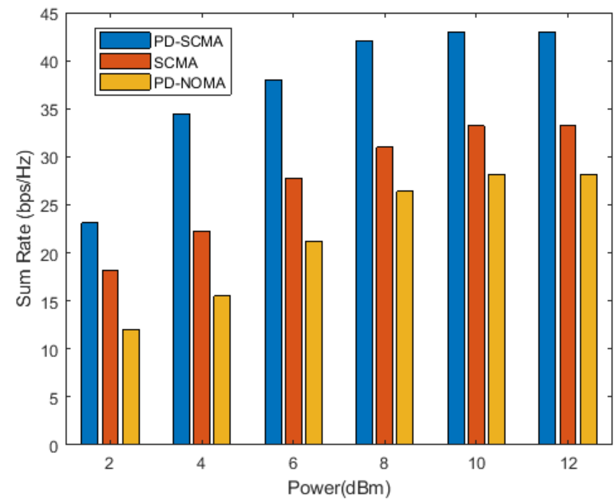

FIGURE 9. Sum rate vs total transmit power using APASO for different MA schemes.

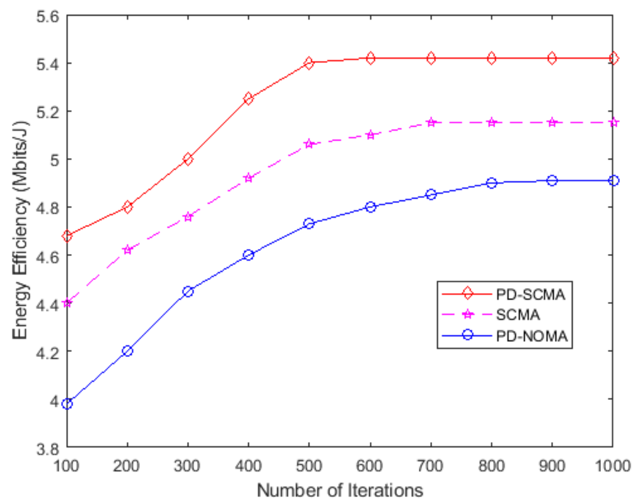

FIGURE 10. Energy efficiency vs Number of iterations for different MA schemes using APASO.

lagrange showing the worst performance. This implies that though the lagrangian algorithm provides better performance in terms of sum rate and energy efficiency, its the least fair.

A comparison of PD-NOMA, SCMA and PD-SCMA RA with application of APASO was investigated and the results of Figures 8 to 10 developed. In Figure 8 the system sum rate versus total number of users is plotted. As it can be observed, the hybrid PD-SCMA has significantly higher sum rate than the other NOMA techniques. Figure 9 shows the system sum rate versus total transmit power for the three MA schemes. The hybrid PD-SCMA outperforms the two conventional NOMA methods. A comparison of the energy efficiency of the three considered MA schemes against the number of iterations is displayed in Figure 10. PD-SCMA is seen to perform better than the other two traditional NOMA approaches. The enhanced performance of PD-SCMA as compared to the conventional NOMA MA schemes can be attributed to the ability of PD-SCMA to merge access features of PD-NOMA and SCMA.

IX. CONCLUSION

In this paper, the performance of nature-inspired algorithms, PSO, ACO and the developed hybrid APASO is investigated regarding sum-rate maximization, energy efficiency and fairness in a hybrid power domain SCMA setup. The investigative results show that the performance of APASO is better than the conventional biological algorithms (PSO and ACO) with respect to sum-rate and energy efficiency. However, ACO is observed to have a higher fairness index than the other considered algorithms. The developed results also show that the common Lagrangian based optimization can lead to system performance overestimation. PD-SCMA is observed to outperform the other considered traditional MA schemes when only APASO is employed for RA. Future work will consider more evolved hybrids with other advanced variants of biological algorithms that have been proven to be efficient in solving NP-hard problems. Furthermore, the performance of succeeding models should feature extended aspects like signaling overhead, channel uncertainty and many others for conclusive deductions.

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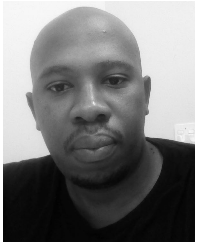

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